



Introduction to Word Embeddings

307307 BI Methods

Converting Words to Numbers

Old Method:- One-Hot Encoding

Each word is represented by setting one dimension to 1 and all the other dimensions to ZEROS.

| id | color |
|----|-------|
| 1 | red |
| 2 | blue |
| 3 | green |
| 4 | blue |

One Hot Encoding

| id | color_red | color_blue | color_green |
|----|-----------|------------|-------------|
| 1 | 1 | 0 | 0 |
| 2 | 0 | 1 | 0 |
| 3 | 0 | 0 | 1 |
| 4 | 0 | 1 | 0 |

Limitations:

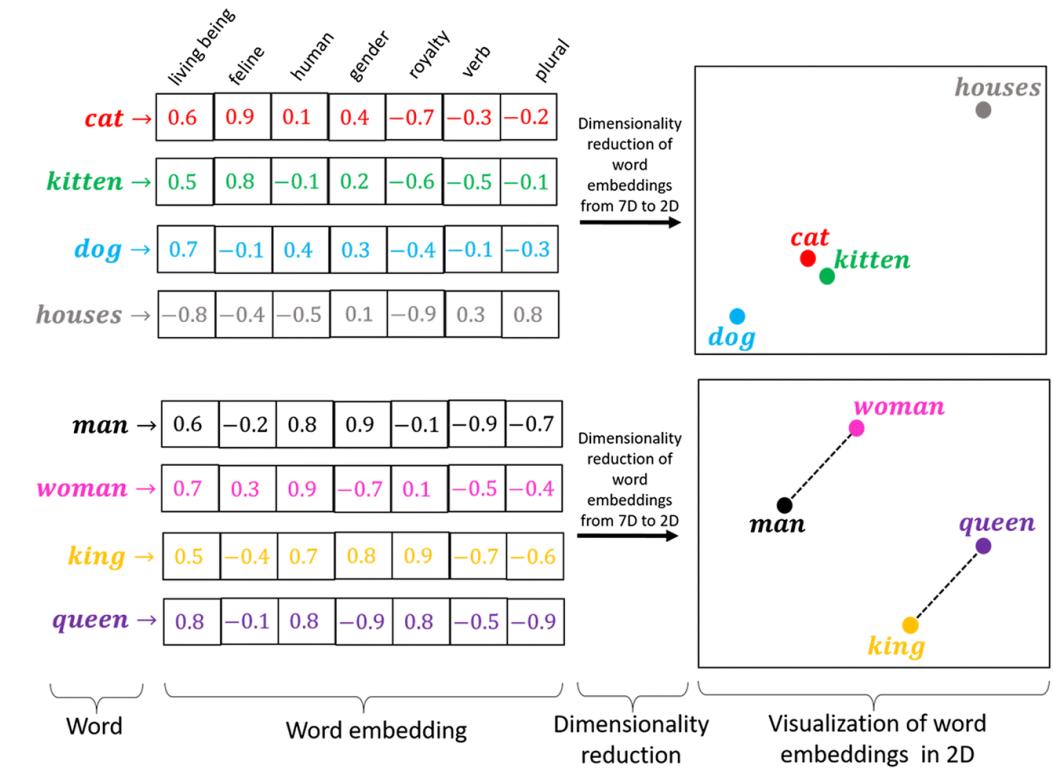
- Vocabulary of 100,000 words → 100,000 dimensions [00100000000000000000000000000000...etc.]
- All words equally distant from each other
- No semantic meaning captured

What are Word Embeddings?

- Capture semantic relationships

Example:

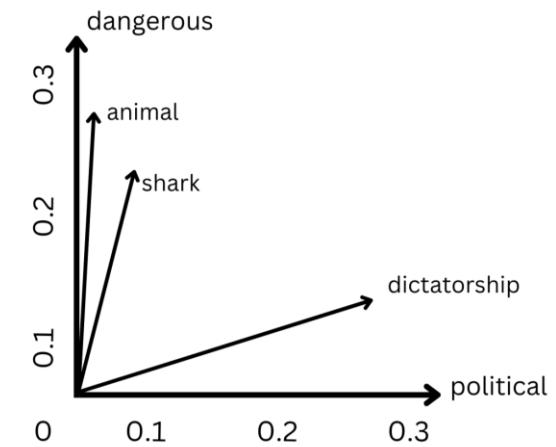
- cat = [0.2, -0.4, 0.7, ..., 0.1] (300 numbers)
- dog = [0.3, -0.3, 0.65, ..., 0.15] (similar to cat!)



Word Embeddings and Vector Spaces

- Words are encoded as dense numerical vectors instead of one-hot or sparse representations.
- Similar words → similar vectors
- Typically, 50-300 dimensions (vs. vocabulary size in 1-hot-encoding)
- Word Embeddings captures **semantic** and **syntactic** relationships about/between words.
- Each dimension potentially captures some syntactic or semantic meaning.
- These vectors are learned from text by models like Word2Vec.

| Word | Dimension 1 (political) | Dimension 2 (dangerous) |
|--------------|-------------------------|-------------------------|
| shark | 0.05 | 0.22 |
| animal | 0.03 | 0.25 |
| dangerous | 0.07 | 0.32 |
| political | 0.31 | 0.04 |
| dictatorship | 0.28 | 0.15 |

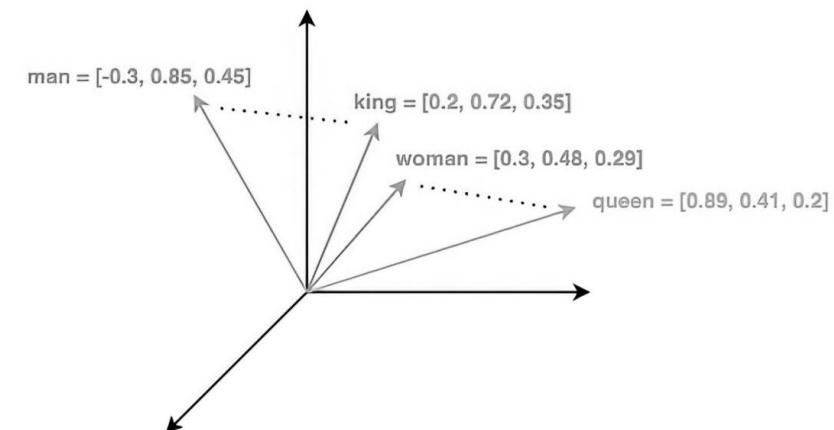
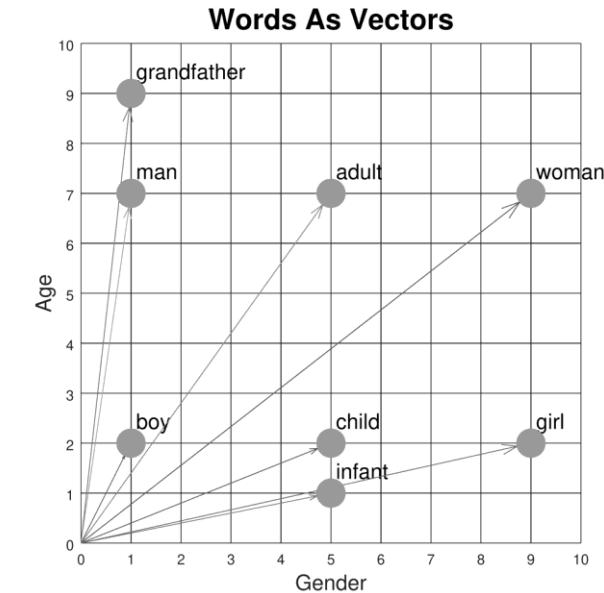


Vector Spaces and Word Embeddings

- A vector space is a mathematical space where each word is represented as a point (or vector) in multi-dimensional space.
- Makes it possible to compare, visualize, and manipulate meanings of words using math.
- Enables operations like:
 - **Similarity:** "king" is close to "queen"
 - **Analogy:** "king" - "man" + "woman" \approx "queen"

Properties of Vector Space

- Semantic relationships are preserved (e.g., "shark" is closer to "dangerous" than "political").
- Similar meanings \rightarrow closer vectors.
- Dissimilar meanings \rightarrow vectors farther apart.



Key Intuition

- Distributional hypothesis - "You shall know a word by the company it keeps" (J.R. Firth, 1957)
- Words in similar contexts have similar meanings:
- "The **cat** sat on the mat"
- "The **dog** sat on the mat"
- "The **rabbit** sat on the mat"
- → cat, dog, rabbit learn similar representations



Word2Vec (Tomas Mikolov et al., 2013)

Word2Vec was developed by Tomas Mikolov and team at Google.

Mikolov presented two architectures:

1) CBOW (Continuous Bag of Words): Predict word from context

- Input: [the, __, sat, on] → Output: cat



2) Skip-gram: Predict context from word

- Input: cat → Output: [the, sat, on, mat]
- Trained on massive text corpora using simple neural networks

Mikolov Approach – Convert Text into Input-Output Pairs

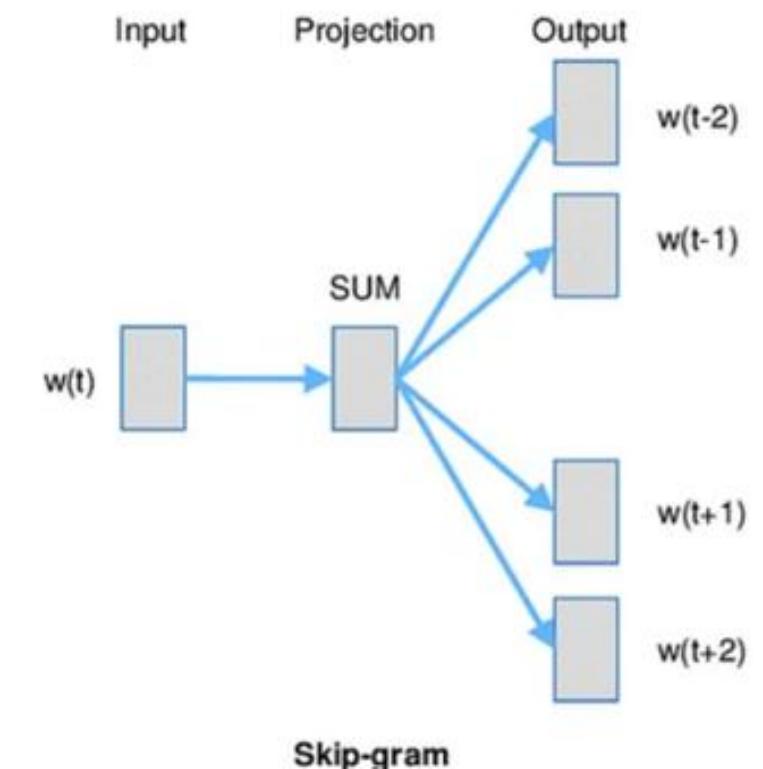
Suppose we have these sentences (corpus), we can convert them into input output pairs to be used for training a neural network.

- "Large language models are transforming business applications",*
- "Natural language processing helps computers understand human language",*
- "Word embeddings capture semantic relationships between words",*
- "Neural networks learn distributed representations of words",*
- "Businesses use language models for various applications",*
- "Customer service can be improved with language technology",*
- "Modern language models require significant computing resources",*
- "Language models can generate human-like text for businesses"*

Skip-gram Architecture

- **Source Sentence:** "Large language models are transforming business applications"
- **Window Size:** 2 (2 words on each side of target word)
- **Task:** Predict context words from target word
- Given Target Word Predict → Context Words

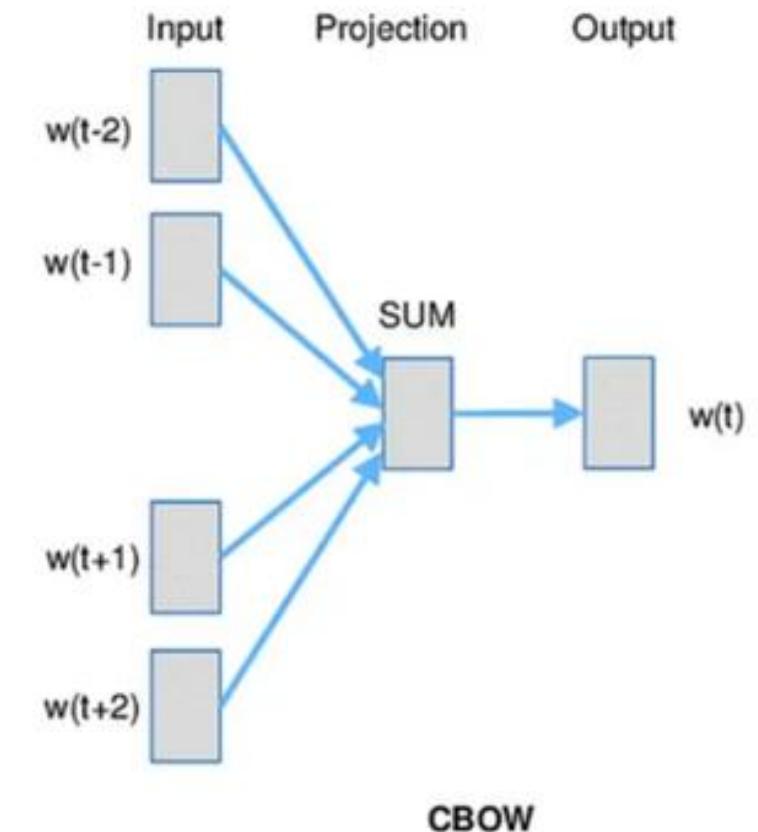
| Input (Target Word) | Output (Context Words) |
|---------------------|--|
| Large | language, models |
| language | Large, models, are |
| models | Large, language, are, transforming |
| are | language, models, transforming, business |
| transforming | models, are, business, applications |
| business | are, transforming, applications |
| applications | transforming, business |



CBOW (Continuous Bag of Words) Architecture

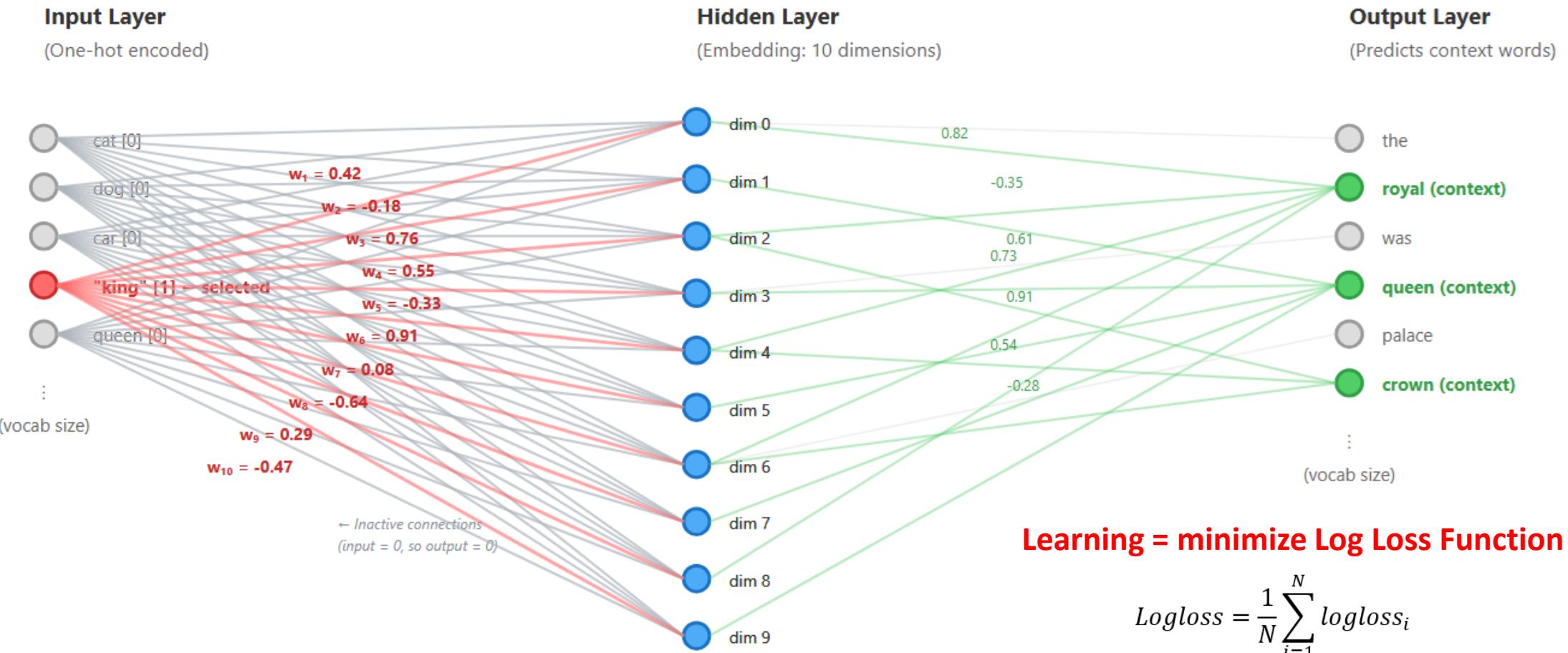
- **Source Sentence:** "Large language models are transforming business applications"
- **Task:** Predict target word from context words
- Given Context Words Predict → Target Word

| Input (Context Words) | Output (Target Word) |
|--|----------------------|
| [language, models] | Large |
| [Large, models, are] | language |
| [Large, language, are, transforming] | models |
| [language, models, transforming, business] | are |
| [models, are, business, applications] | transforming |
| [are, transforming, applications] | business |
| [transforming, business] | applications |



Word2Vec Skip-gram: Learning Word Embeddings

Training sentence: "The **king** wore a royal crown, and the queen stood beside him"

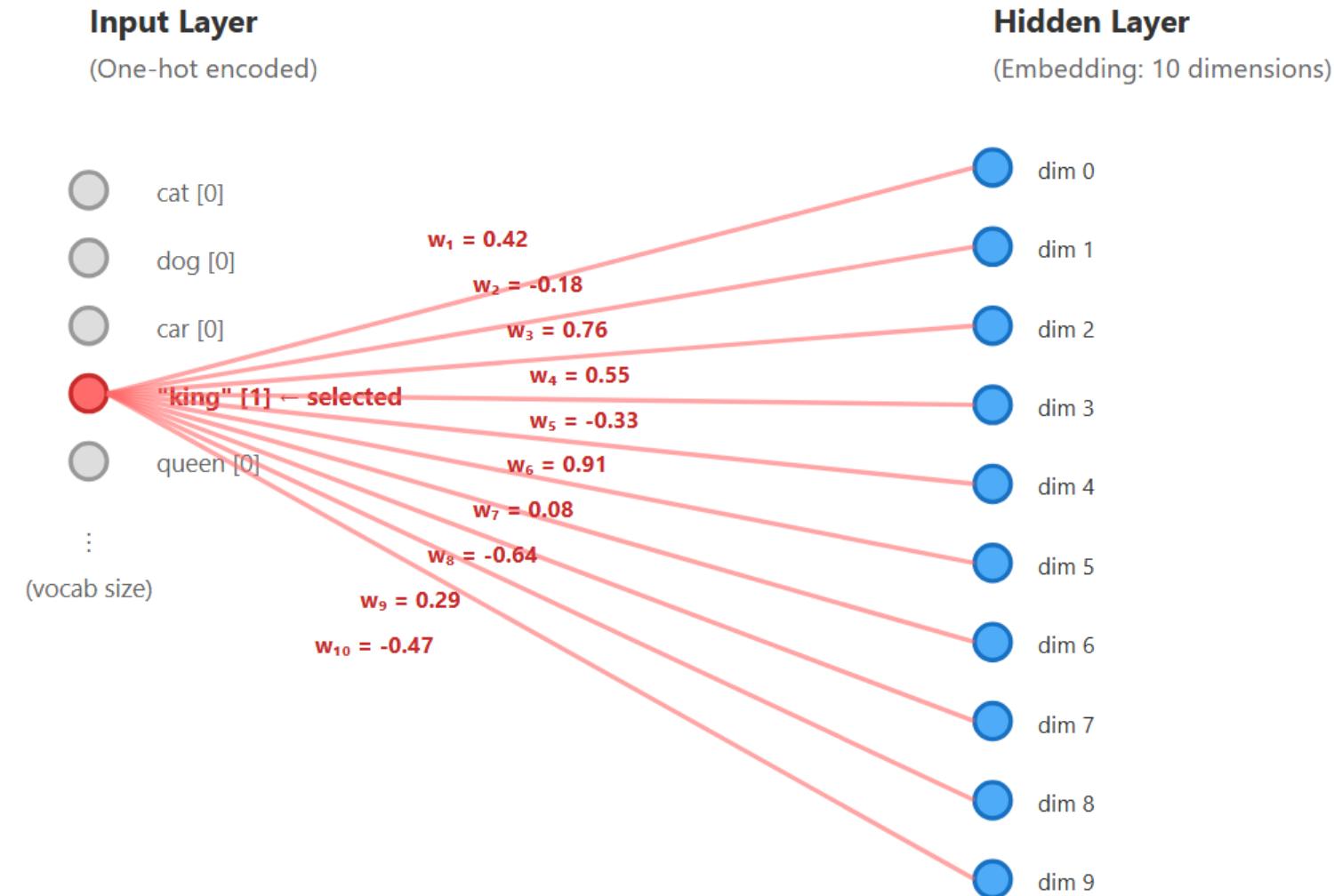


Training Process: Input Word "king" → Embedding → Predict Context Words

- Input → Hidden weights = Word Embeddings (e.g., king = [0.42, -0.18, 0.76, 0.55, -0.33, 0.91, 0.08, -0.64, 0.29, -0.47])
- Hidden → Output weights predict context: Given "king", maximize probability of "royal", "queen", "crown"
- Backpropagation updates both weight matrices → words in similar contexts get similar embeddings



Skip-Gram Model



Measuring Similarity Between Word Vectors

Why Compare Word Vectors?

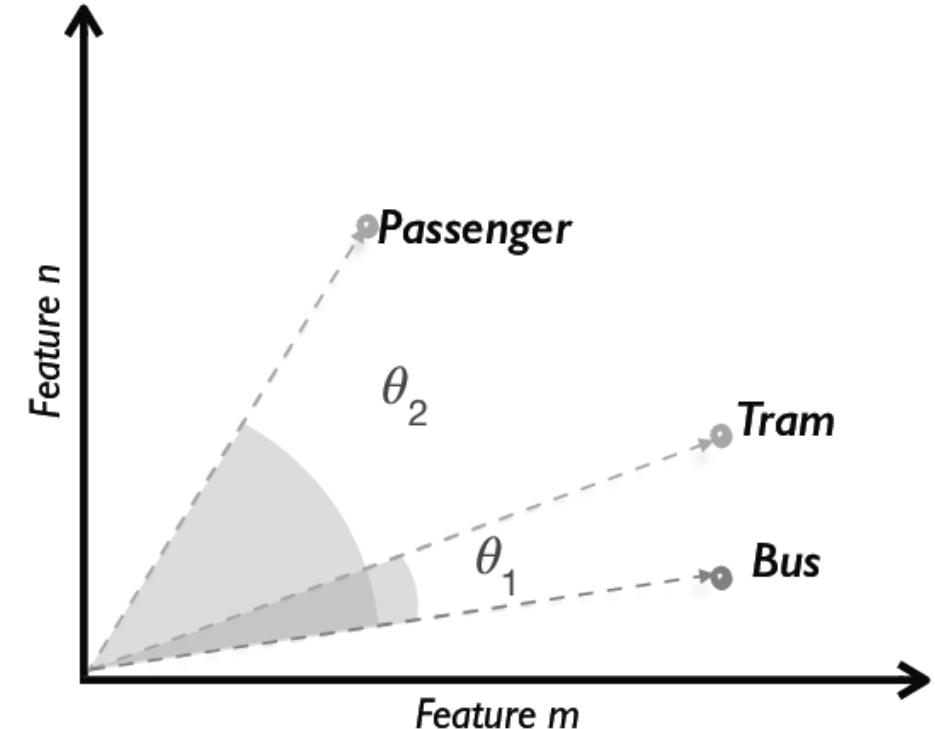
- Word embeddings map words into a vector space.
- Words with similar meanings** are placed **close together** in that space.
- To quantify this "closeness," we use **vector similarity**.

Cosine Similarity

Most common metric used to compare word vectors:

$$\text{cosine_similarity}(\vec{A}, \vec{B}) = \frac{\vec{A} \cdot \vec{B}}{\|\vec{A}\| \|\vec{B}\|}$$

- Measures the **angle** between two vectors (not their magnitude).
- Ranges from **-1 to 1**:
 - 1 → Same direction (very similar)
 - 0 → Orthogonal (unrelated)
 - 1 → Opposite directions (very different)



Intuition

- Vectors for "king" and "queen" will have high cosine similarity.
- Vectors for "apple" and "keyboard" will have low similarity.

Use Pre-Trained Embeddings

Gensim is an open-source Python library used for **topic modeling** and **natural language processing (NLP)**. It's great for working with **large text datasets** because it doesn't need to load all the data into memory at once.

Key features:

- Builds and uses **word embeddings** (like Word2Vec, FastText, Doc2Vec).
- Measures **semantic similarity** between words or documents.
- **Efficient and memory-friendly**, ideal for handling big collections of text.

```
import gensim.downloader as api
from gensim.models import Word2Vec

# Load pre-trained Word2Vec model
word2vec_model = api.load("word2vec-google-news-300")

# Get vector for a word
cat_vector = model.wv['cat']
print("Vector for 'cat':", cat_vector[:5]) # Show first 5 dimensions

# Find similar words
similar_words = word2vec_model.most_similar('computer',
                                             topn=5)
print("Words similar to 'computer':", similar_words)

# Word analogies
result = word2vec_model.most_similar(positive=['woman',
                                                 'king'],
                                         negative=['man'],
                                         topn=1)
print("king - man + woman =", result)
```

Applications of Word Embeddings in NLP

1. Semantic Similarity

Measure how similar two words, phrases, or documents are by comparing their vector representations.
Example: Identifying that "doctor" and "physician" are closely related.

2. Text Classification

Used as input features for tasks like spam detection, sentiment analysis, and topic classification.
Embeddings provide rich, dense input for machine learning models.

3. Named Entity Recognition (NER)

Help identify proper nouns and classify them into categories like person, location, or organization.
Embedding-based models improve contextual understanding of named entities.

4. Machine Translation

Map words from one language to another by aligning embeddings in multilingual space.
Improves translation accuracy by leveraging semantic proximity.

5. Question Answering & Chatbots

Used to understand queries and match them with appropriate answers or responses.
Enable bots to interpret intent and context more accurately.

• 6. Information Retrieval

Enhance search engines by retrieving results based on semantic meaning, not just keyword matches.
Example: Searching for "heart attack" returns documents containing "cardiac arrest."